Predicting the Progress of Vehicle Development Projects: An Approach for the Identification of Input Features

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Abstract: Today project managers estimate time and other project relevant key performance indicators by using project management tools e.g. milestone trend analysis. We believe that predicting the project's progress with traditional methods will soon reach its limitations due to the increasing complexity in vehicle development. Machine learning methods provide one possible solution. The vision is to predict the progress of development projects in the early stages of the project. In order to make this vision come true, we need to define measurable input features for machine learning models. In this paper, we focus on representing an approach to identify parameters that exert influence on the progress of development projects.

1 INTRODUCTION

For many customers, the quality of a product is one of the key factors in a purchase decision. As a result, many brands within a market try to differentiate themselves through this purchase criteria. In addition to the constantly growing demands from the competition and from the consumers and the government (Deloitte, 2019), the challenges in the development of innovative products also grow with the advancing technological progress. By now more than 90 percent of all future vehicle innovations are located in the field of electrical/ electronics development, the search for errors and the sustainable correction of them contribute greatly to the success of the project.

With the considerable increase in the functional integration of the electronic control units (ECU), the complexity of product quality management increases considerably, since the system behaviour is no longer deterministic. This refers in particular to the interaction of the ECUs in the overall interconnection. Each component is known exactly, but a prediction of its state of integration cannot be made with great certainty. For example, a new software delivery of a highly interconnected ECU can result in a new function in the vehicle, while at the same time some other functions are no longer available due to regression in the software.

Furthermore, the products may be developed in better quality, at lower costs and in less time. The requirements for error elimination and minimization are increasing. At the same time the demands on meeting deadlines are increasing, as milestone shifts often result in considerable additional work and costs, an extension of the project duration or in a reduction in the scope of services. From our experience, as industrial engineers working in a German car manufacturer, we have accompanied the course of a large number of vehicle projects and derivatives from the perspective of electrical/ electronics development. In many cases we were able to observe that a prediction of the project duration with traditional methods could only be made insufficiently or with great uncertainty. Depending on the project's complexity either temporal deviations in the function development or in the reduction of errors may occur, because the courses of past vehicle projects were not sufficiently considered.

Nowadays on the other hand, we can already see numerous applications from the field of artificial intelligence (AI) where historical data is used to predict future outcomes, e.g. sales forecasting,

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predicting stock prices or churn analysis. Many of these applications are already on an almost human expert level, e.g. early diagnosis of diseases based on X-ray images or AI-based translation of languages (Kermany et al., 2018); (Hassan et al., 2018). This leads to the question of whether the usage of methods from the field of AI can also be used for the prediction of the project's progress, which is exactly our scientific vision. Having a system like this, the risks of shifting elementary project milestones in the early phase could be recognized in order to create the preconditions for steering the project into an orderly path again. This ambitious goal requires not only the definition of project's progress, but also the identification of indicators and factors that exert influence on the progress of development projects.

With this contribution we intend to identify indicators that are suitable for the use in machine learning scenarios. This approach will be presented on the use case of the electrical/ electronics development of a car manufacturer.

For this purpose, Section 2 provides an overview of project success models and critical success factors as a result of a broad literature research in order to identify possible general starting points for input features. Section 3 presents the research method, an employee survey on the topic of project success in the electrical/ electronics development department. With a precise view on the research area, the starting points identified in section 2 will help to extract the domain knowhow and to find possible input features for the use case. Section 4 compares the results from the literature research with those from the employee survey. With regard to applicable input features for machine learning models, a critical look is taken at the analysis results. A summary and further proceedings are presented in section 5. An overview of the identified input features is given. Finally, a recommendation for further work is given and as a scientific vision the concept of our machine learning approach is presented.

2 RELATED WORK

Based on the vision of being able to predict the course of vehicle development projects, we first need to identify the right measurable factors influencing the course of the project. Therefore, in this section we will take a look at literature for applied machine learning approaches in project management and project management literature regarding the concept of project success as well as critical success indicators.

2.1 Applied Machine Learning

Looking at applied machine learning the number of approaches has been increased greatly during the last 20 years. By now there are also various applications for machine learning in project management that have been discussed in literature. Popular approaches are for example: estimation of software development effort (Srinivasam and Fisher, 1995), early life cycle cost estimation (Boetticher, 2001), machine learning in scheduling (Aytug et al., 1994), software project risk management modelling (Hu et al., 2007), predicting the priority of reported bugs (Sharma et al., 2012) and software requirements prioritization (Perini et al., 2013). Interestingly our literature research did not reveal the use of any machine learning algorithms applied in the early life cycle for the estimation of development project's progress in the automotive sector. Since the complexity of product development - driven by increased requirements due to intensified competition, regional regulatory requirements and market-specific customer wishes - is considered to be higher than in projects from other industrial sectors, the automotive industry demands a tailor-made approach. Though the available literature focuses on very specific approaches for time estimation in projects for various industrial sectors except automotive.

Huang and Chen developed a framework for estimating the project completion time. Their framework starts with collecting data such as project task structure, task relations, and quantified team member characteristics in order to analyse the influence of these factors on the project completion time. Further a simulation model is used to assign the identified tasks dynamically to the team members according to their knowledge level and other factors. After several iterations the final value of time is estimated. Finally, they analysed the data to identify significant factors influencing the project completion time (Huang and Chen, 2006). While this framework also deals with the analysis of influencing factors on the project duration, the approach does not offer an opportunity for adaptation into a machine learning approach. Accordingly, the proposed method of Huang and Chen is more suitable for low complexity projects and therefore not suited in the scope of this paper.

Another approach was published by Pedroso. He proposed a system that aimed to help improving the planning process in project management by performing risk analysis. Therefor instance-based learning and regression models were used, which gave satisfiable results when applied on real-world scenarios (Pedroso, 2017). With this Pedroso has developed an interesting approach to predict risks for future projects based on the work history of a specific project manager. However, a transferability to the context of vehicle development can be doubted as the approach lacks the ability to capture global patterns. It is assumed that only the identification of cross-project features will allow a prediction of project's progression in the required quality.

Li et al. developed a method for time estimation in ship block manufacturing. By using the k-Means algorithm the researchers clustered the different ship blocks according to their features (e.g. length, width, depth, weight, form etc.). Afterwards and in order to evaluate the planned time of each cluster, Li et al. used a data envelopment analysis model. By processing the calculated results an estimation for the manufacturing planning was accomplished. Thereby, they used a genetic backpropagation neural network to capture the knowledge for reuses (Li et al., 2019). With their approach, Li et al. were able to predict the manufacturing time of a ship by forecasting the respective times for the production of a single ship block and then adding these times considering the number per block type. Unfortunately, the identification of the relevant features has not been described in detail by the authors. Thus, this approach is strongly industry- and business-specific. It can only be transferred to a very limited extent to another business area (development) of another industry (automotive engineering). Finally, the approach does not consider the high complexity of automotive product development, resulting primarily from interconnectivity and the collaboration of ECUs on different vehicle architectures.

Ahmed et al. discussed a method for the estimation of the procurement time of Public-Private-Partnerships projects. By using multiple regression models, they compared the predicted procurement time with secondary data from the World Bank (Ahmed et al., 2019). With regard to the identification of factors that can cause a delay in PPP projects, Ahmed et al. conduct a literature search and evaluate three case studies. As with the other approaches above, these are industry-specific factors. In addition, the scope of the referenced projects is only set up to the procurement of resources. The true complexity in the temporal forecast of projects begins however, due to its characteristic uniqueness, with the operational start of the project.

2.2 Defining Project Success

The concept of success in project management and its composition are topics that have in principle been of interest to the research community - and naturally also to practice - since the beginning of the development of project management as an independent discipline (Jugdev and Müller, 2005). Not without reason it is called the most discussed topic in the world of project management (Shenhar et al., 1997).

The analysis of various papers shows that many researchers have common intersections. In the research period between 1960 and 1980, researchers concentrated mainly on the “magic triangle” (cost, time and quality) (Atkinson, 1999). In the period from 1980 to the turn of the millennium these factors retain their essential role in measuring project success and are simultaneously extended to include stakeholder satisfaction (e.g. end customer, end user, etc.) as well as the benefits for stakeholders and the supporting organization resulting from the project. This research direction is now accompanied by an awareness between the project implementation phase and the success of the project after the end of the project (Pinto and Slevin, 1988) (Wuellner, 1990) (Pinto and Pinto, 1991). From between 1990 and the 21st. century onwards, strategic goals and overall business success increasingly play a decisive role as the validity of the research continues and the success factors determined up to this point are taken as a basis. Projects are also increasingly being evaluated on the basis of specific definitions of success and failure related to the individual project (Navarre and Schaan, 1990) (Shenhar et al., 1997) (Baccarini, 1999). It should also be mentioned that, depending on the domain, additional criteria such as safety or environmental friendliness are also included (Kometa et al., 1995) (Kumaraswamy and Thorpe, 1996).

Different researchers have identified different success criteria. One possible cause may lie in the different domains themselves. Just as the requirements for products from different industries vary, the domain-specific project success criteria could also be divergent.

2.3 Critical Success Factors in Projects

In contrast to project success indicators, critical success factors (CSFs) are all those activities that are intended to ensure the success of organizations and projects when properly implemented (Boynton and Zmud, 1984). Müller and Jugdev also define them as those elements and independent variables which, when influenced, increase the probability of success of projects (Müller and Jugdev, 2012).

Since the beginning of the activities in this research field, a large number of researchers in various industrial sectors and countries have been dealing with critical success factors in projects (CSF). A comparison of the various publications shows that a certain set of CSFs is repeatedly highlighted.
In the research period up to 1980, the researchers identified a precise project definition with clearly defined objectives, detailed and realistic project planning and effective project monitoring and controlling as the most important CSFs. Furthermore, the technical and leadership skills of the project manager and the project team, effective communication during the project and support from top management are the most important factors (Pinto and Slevin, 1986) (Pinto and Slevin, 1988) (Belassi and Tukel, 1996).
The evaluation of the following years up to the turn of the millennium confirms the results of the analysis. The technical and leadership competencies and the support of the management board rise in the ranking list of the most frequently mentioned CSFs to the ranks one and two. The following ranks reflect the factors from previous years. But also, the understanding for the needs of the project customer e.g. attained by the active integration of the product's user seems to become ever more relevant for enterprises of all sectors (Fortune and White, 2006).
The above impression can also be confirmed by looking at the research period up to 2010. The CSFs identified over the past ten years could be repeatedly identified during this period in a slightly changed ranking order. A look at the following years repeatedly confirms the research results from the beginning of the observations. Those who manage their projects with clear goals, precise planning and effective monitoring, risk and change management obviously have good prospects for project success. If this skill set can now be paired with technical and leadership skills in the project team, effective communication and sufficient resources, the probability of success can be increased again. In addition to a good understanding of the customer's needs, for the first-time researchers are also counting positive relations to politics and society among the most frequently mentioned critical success factors.

3 RESEARCH METHOD

After having looked at the project management literature, we now carry out a precise analysis of the application case. In order to extract the domain specific knowhow in the related research area we designed a questionnaire to conduct an employee survey. For this survey a group of 80 participants were asked on different aspects of time-related and process-oriented factors and about widely known critical project factors in their individual working environment. To make sure of getting knowledge from experts, only participants with at least ten years of working experience in electrical/ electronics development were chosen. In addition, attention was paid to a heterogeneous group composition (e.g. age between 30 and 60+). These experts were selected on the basis of their individual role (e.g. executives, project managers, test engineers), their project affiliation (e.g. small size projects, medium size projects, full size projects) and their responsibility within the specific project (either development or test and integration), all to make sure, that we will receive every possible perspective on the project's pasts.
For this questionnaire, we identified 17 items to test the research area for the presence of critical success factors. This includes a strict project planning, the consequences of non-compliance with milestones and processes in the early project stages or a delay in assigning suppliers. Late concept decisions, the management of risks and the support of top management are also examined. It is also analysed whether the scope of services, the technical specifications, the employee satisfaction or a stable internal company policy contributes to the success of the project. For each statement in the questionnaire we asked the participants on a scale from 1 ("does not apply at all") to 5 ("is absolutely true"), how applicable this statement is. In order to avoid false statements as far as possible, the participants were also given the opportunity to choose "don't know" or "not specified".

4 FACTORS INFLUENCING THE PROJECT'S PROGRESSION

The analysis of the relevant literature on applied machine learning from section 2.1 has shown that there are only few and very specific applications in project management at the moment. This shows the great potential that the applied machine learning has in the field of project management. At the same time, this also shows a large research gap.

4.1 Examination of Project Success Indicators

Since the problem of predicting the progress of vehicle development projects is a highly interdisciplinary one, the relevant project management literature between the 1980s and today was examined with regard to the concept of project success and critical success factors.

From this we can see that there is a lack of a universal definition of project success. This leads to the need for a working definition on the basis of which the continuation of further research activities can be built. For this purpose, the project success indicators identified in section 2.2 are combined into clusters and then analysed for their relative frequency (figure 1). The results show that the classical success indicators such as costs, time, quality and scope of services can be counted among the most frequently cited. Furthermore, it can be read from the results that the right management of stakeholders (customers, clients and project managers and employees) can be an indicator for a successful project. However, project-specific topics such as effectiveness in implementation and technical specifications are also regarded as indicators of success by 40 to 50 percent of researchers. Restricting the focus of the study to the period from 2010 onwards confirms the above evaluation in most of the citations. Factors that have been confirmed since then are revenue, profit and strategic factors such as the development of new market shares or new markets, further the development of the organization or the increase in competitiveness can now be found with a high relative frequency. After it used to seem sufficient to complete projects in the right time, at the right costs, in the right scope and with the right quality, now a measurable “return on investment” is increasingly coming to the fore.

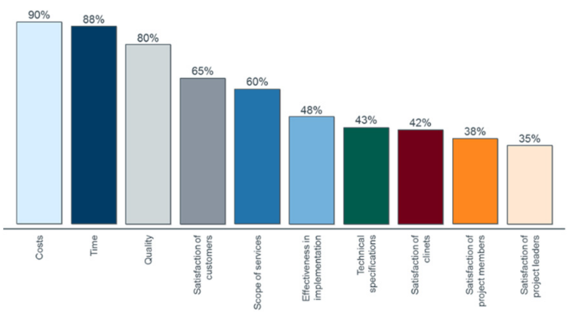

Figure 1: Top cited project success indicators ranked by relative frequency.

Based on the framework of this work and the scientific question at the core, only those indicators will be considered for further activities that can generally measure the success within the project implementation. Since indicators such as customer satisfaction and client satisfaction, revenue or profit and the possible development of new market shares can only be measured during or after the project handover or within the context of the use of the resulting product, these indicators should not be considered here further. Similarly, the satisfaction of the project managers shall be excluded, since they define the project success by the fulfilment of the defined project goals and their satisfaction can therefore only be measured at the end of the project. Furthermore, the costs as an indicator for the success of the project shall not be further considered, since these are triggered indirectly via budget and resource availability in the research area. From this limitation a working definition for the project success (figure 2) can be deduced. With regard to our vision, the prediction of the project’s progress, the quality, the scope of services, the technical specifications, the effectiveness/ efficiency in project implementation and the satisfaction of the project team members shall be defined as primary success indicators.

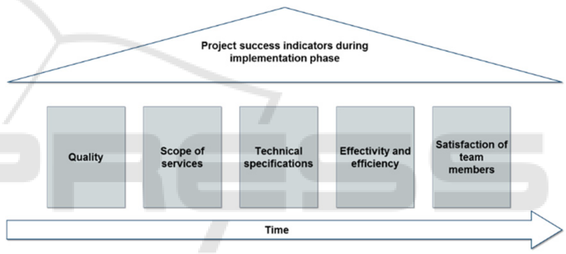

Figure 2: Working definition project success indicators.

As described in section 1, the success of a vehicle development project is to be measured from the perspective of the electrical/ electronics development department. For this concrete use case, the project success therefore requires a defined scope of services to be achieved and a minimum of customer-relevant residual errors to be present at the end of the project. All projects for which either the scope of services has been reduced, the project duration has been extended or an unreasonably high number of residual errors are present at the end of the project are therefore classified as unsuccessful.

4.2 Analysis of Critical Success Factors

In addition to the examination of the project's success, we analysed the relevant literature between 1960s and today with regard to the concept of critical success factors for projects. Again, we clustered and examined the findings from section 2 according to their relative frequency (figure 3). Results show, that the existence of the right competences and skills, a

clear goal and realistic planning are fundamental factors for successful project implementation. In addition, more than half of the researchers surveyed consider top management support and effective communication to be decisive success factors. Other relevant characteristics were an understanding of customer needs, the availability of resources and the existence of common management systems (project controlling, change and risk management system).
Interestingly, if the range of the analysis is reduced to the period of 2010 and after, the set of success factors is almost identical. While top management support is no longer one of the ten most cited success factors, social and political factors are among the second most cited criteria. Realistic project planning is still seen as a relevant instrument for project implementation. More than 90% now also name the implementation of a risk management system as a critical success factor.

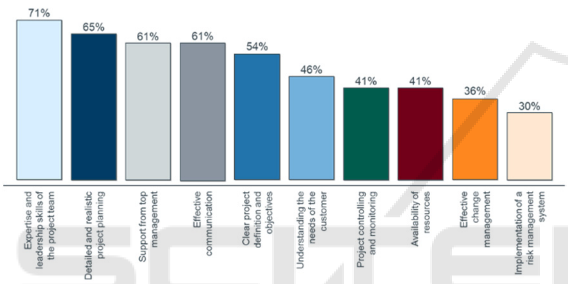

Figure 3: Top cited CSFs ranked by relative frequency.

A possible explanation for this could be the increasing and rapidly changing demands of customers, competition and politics. This can also be measured by the fact that effective project controlling and change management are becoming increasingly important. Good communication and an understanding of customer needs are now enumerated by 75% of the researchers. After all, almost six out of ten researchers consider clear project goals and the availability of resources such as budget, technology and logistics to be decisive success factors.
In conclusion, this analysis shows that many of the identified CSFs seem to have cross-project applicability. One possible explanation for this is that CSFs embody a success-oriented definition of the project framework or project environment and are only indirectly linked to the operative results of the project. In addition, a large number of possible influencing factors were found that could serve as possible input features.

4.3 Evaluation of the Employee Survey

In addition to the broad literature research, we conducted an employee survey in the research area. Results show that the project success indicators found in our literature research were confirmed within the scope of this survey. Accordingly, 86% of the participants agreed with the assertion that the technical specifications of a vehicle development project can have an influence on the success of the project's progress. Three-quarters of the respondents confirmed efficiency in implementation as a success indicator, and just over half attribute a major role to product quality and employee satisfaction. In addition, 43% of those surveyed rated the scope of services as an indicator of project success. Only 14% of the respondents rated the planned duration of the projects as the least strongly involved in the success of the project. The reason for this lies in the planned target development time of a vehicle project that always has a constant length of 48 months.
Following the introductory questions on the success of the project, the participants were confronted with the objectives and deadlines. It can be seen from the survey's results that a strict and detailed project schedule is kept up to date in less sub-projects. Furthermore, the assertion from previous expert interviews could be proven quantitatively (95%) that delays in the awarding of suppliers have a negative effect on a timely development. Also, 95% of the participants agreed that on the one hand the risk of later milestone shifts increases considerably if deadlines are not met in the early development phase. On the other hand, late concept decisions have a negative impact on the deadline targets of vehicle development projects as well. More than three-quarters of the respondents also stated that process adherence in the early project phases can be a success factor with regard to deadline targets.
Furthermore, we asked for specific critical project success factors in the closer meaning. Based on the responses of the participants (62%), the research area is currently less able to learn from past mistakes. In contrast, there was predominantly indifference as to whether project risks in the research area were identified early, evaluated and documented with measures and pursued. Feedback on the question of top management support for acute challenges continued to be widely distributed. 69% of respondents believe that the use of proven technologies would facilitate the development of vehicle projects. This can be an indication that different vehicle development projects are also based on different factors influencing project success.

However, most of the CSF already identified in theory could also be quantitatively confirmed by the study. As a result, 69% of respondents estimate that the use of proven technologies would facilitate vehicle development. 90% of the participants agreed that good performance in cooperation with suppliers contributes to the success of the project. Furthermore, 81% of the participants agreed that the number of functions have an influence on product quality, e.g. the number of customer-relevant errors. This is in contrast to the few mentions that the scope of services can influence the success of the project. Absolute agreement (100%) prevails that both the mere number of new functions and new technologies in vehicle architecture or new highly networked components always present a major challenge for the planned development and validation. Conversely, this also means that the probability of success is higher for projects in which a large number of components and/or functions are taken over from other projects. With 90% of votes in each case, the general employee satisfaction and a stable, departmental internal policy can be counted as CSF. The size and complexity of the project was also clearly mentioned (100%) as a CSF.

Table 1: Risk factors for the project success.

Project success indicators	Risk factors
Time	- Late decisions by the top management on changes to volumes already developed - Late nomination of suppliers - Delays in the function buildup and in the function experiencability
Quality	- Less prioritisation of vehicle projects in favour of Prio1 projects
Technical specifications	- Specification for components or systems not up to date - Exchange of suppliers for the advancement of control units - Too many different platforms - Unclear or unrealistic requirements - Misinterpretations regarding the use of old technology or platform for new launches - Misjudgements in launches with a great portion of carry-over-parts
Effectivity and efficiency in the implementation	- Lack of communication and coordination in top-down decisions - High bureaucratic effort for changes in the project - Postponement of important decisions - Missing role descriptions and task distributions
Satisfaction of project members	- Too much tracking - Overhang to task force operation - Too few resources in personnel or competence

Finally, the interviewees had the optional opportunity to name further factors, which from their individual point of view could risk the timely development and safeguarding of vehicle projects. The identified risks were gathered in table 1 and assigned to the defined project success indicators. Interestingly, late decisions, either with a general reference to the project or already when awarding contracts to suppliers, appear to represent a major risk for the schedule targets. Additionally, the progress of the function build-up or the functional perceptibility can be an important indicator of project's progression. Furthermore, we learnt from the survey that downgrading projects in the decision-making processes influence the quality of the products negatively. Also, we identified the change of suppliers in the further development of ECUs as a relevant risk. A surplus of reporting and task force operations appears to have a negative effect on employee satisfaction. Finally, with unclear goals, inadequate communication, missing cooperation models, too few resources and high bureaucratic hurdles, many CSFs known from theory were once again recognized.

Principally, the identified factors show a good applicability for machine learning models. Among the examples mentioned above, we can identify numerical data, meaning continuous or discrete data, e.g. the average number of persons per project, number of shifts in the perceptibility of functions and so on. Furthermore, there is a lot of categorical data, e.g. exchange of suppliers for the advancement of an ECU, project size and so on. And finally, we can make use of a lot of time series data. After initial analysis of the data, it can be confirmed that this information is available in a sufficiently large quantity and is complete except for a few gaps. Using feature engineering methods, we will address this problem later. This means that the data will provide the basis for e.g. approaches of multivariate prediction problems. Furthermore, we are able to use the labelled information for classification problems. Depending on the specific issue, the data can also be used for clustering purposes. From this it can be concluded that the information available to us will provide a very high usability for the application in machine learning approaches.

5 CONCLUSIONS

With this paper, we have presented a procedure to identify measurable factors that influence the course of vehicle development projects in order to use them as input features for machine learning models to predict project's progression. To achieve this goal, a broad literature research about applied machine learning was conducted. It turned out that there is still a large research gap on machine learning applications in operative project management. Furthermore, the relevant project management literature was analysed with regard to the different models of project success and critical success factors in projects. As a result of these investigations, the most frequently cited project success indicators and CSFs have been identified. The overviews of the indicators of project success and the CSFs that emerged from the literature research do not only provide a valuable list of possible influencing factors. They also provide valuable information that are extremely helpful to project

managers from all industry sectors in the initialization and definition phase of a variety of projects.
At the same time, an analysis of the project success and the CSFs provided a more precise view of the use case. The results of the literature research could be confirmed for the use case. These results were then used to develop a working definition for the success of the project in the implementation phase. With regard to the applicability as input features in machine learning models these findings were consolidated. Finally, concrete examples from the use case were assigned to the identified success indicators (figure 4). In addition to the identified CSFs, a large set of influencing factors on the course of vehicle development project in the research area has been identified.

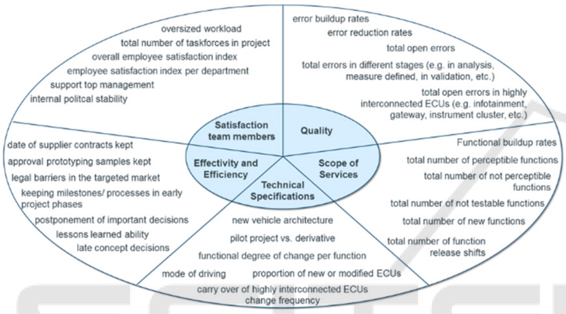

Figure 4: Extract of influencing factors on vehicle development project's progressions.

Our long-term objective is to develop a general framework for the prediction of development project's progressions. The basic idea of the planned procedure is shown in figure 5. Hence, the next step is to build an adequate DataSet containing the identified input features. Therefore, it must be checked whether the data are quantitatively recorded and whether accessing can be established. Furthermore, it has to be clarified how to deal with information that is not yet recorded. Here we expect to have data from different databases and about various car projects. We will have access on general project-relevant information (e.g. start and end dates, milestones, number of functions, size and complexity, amount of ECUs, technical specifications, soft facts, etc.), time series data about function releases and error handlings (e.g. car project, ECU, responsible department, time to build-up functions, time to bug fix, market, etc.) and additional data (e.g. date of contracts with suppliers, employee satisfaction, etc.).
As projects are characterized by their uniqueness, it is assumed that the effects of the input features on the course of the project can vary between the various projects. Based on this, the influencing factors in relation to the vehicle projects must be examined precisely. The findings from section 3 support this assumption, since we found out, that there may be different factors that can possibly influence a vehicle development project. Therefore, we will analyse whether the influence of the features is different or not at different phases in the course of the project. For this reason, we will apply feature selection methods on our data (with focus on filter and wrapper methods) and compare the results with those from this paper to generate a dataset for further use.

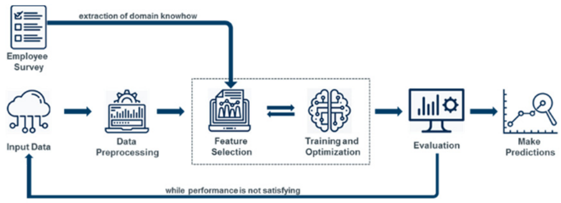

Figure 5: ML-Approach for predicting project maturity.

Within the research area, automotive development projects are mainly divided into two categories: SOP and LCM projects. Based on domain knowhow there is evidence that in many cases the course of SOP and LCM projects seems to be different. This implies different factors that influence the course of the project. To predict the progression of a project, it is therefore valuable to know beforehand whether the project's progression to be predicted is an SOP or LCM project. In this context, an approach for the classification of vehicle development projects shall be developed, taking into account common methods (e.g. kNN, LSTM, Random Forest, SVM, ...).
Finally, we plan on implementing different models for time series forecasting (e.g. random forests, recurrent neural networks, convolutional neural networks, …), in order to predict the further course of the project. Special attention shall be given to the prediction of the function build-up and the error reduction. The model that represents the best performance based on the selected evaluation metrics will then be selected. For a milestone to be defined, a measurement is then to be made as to whether the vehicle project can withstand the requirements of this milestone and whether it can be classified as successful. Finally, the model will be verified on the use case of a present vehicle development project with regard to its effectiveness by making predictions about the project's progressions.

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